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ORIGINAL RESEARCH OR TREATMENT PAPER

Phenotypic Trait of Painting Cracks

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ABSTRACT
A painting, like human skin, develops cracks on the surface as it dries and ages. The painting cracks, also known as craquelure, are often considered analogous to human fingerprints; these have been regarded as a unique signature reflective of the painting's characteristics and are important in art authentication. Intriguingly, studies in other fields, such as geology, have observed the presence of distinctive characteristics in soil desiccation cracks. These cracks exhibit self-similarity, forming patterns that suggest broader geological processes at work. In light of this connection, the primary objective of this study is to investigate whether the painting cracks also exhibit a self-similar nature. By delving into this, we seek to shed light on the underlying properties of the painting cracks. This study also aims to investigate whether the characteristic self-similar trait of the cracks can serve as an identifier in relation to the provenances of the paintings. To this end, this study adopts the methodology originally designed to characterize the phenotypic traits of 3D particle geometries in granular materials research. This study develops a 2D equivalent concept, focusing on the phenotypic traits of the individual islands enclosed by cracks within paintings. The results successfully demonstrate that the phenotypic trait of painting cracks exhibits a self-similar nature, which can reveal characteristics associated with the provenances of paintings. The findings will offer valuable insights into the scientific examination of artworks based on painting cracks.

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KEYWORDS
Painting cracks; craquelure analysis; phenotypic trait; self-similarity; power-law; art authentication

Introduction

A painting is like human skin in some sense. Just as genetic makeup leaves unique physical characteristics on our skin such as fingerprints, painting cracks known as *craquelure* have been recognized as an important characteristic of a painting that may serve as a unique identifier. The cracks naturally manifest on the surface of a painting due to drying and aging (Krzemień et al. 2016). The drying cracks (desiccation cracks) begin to form within the first few weeks after applying paint, as volatile solvents evaporate from the painted surface. This process is strongly influenced by factors such as adhesion to the sublayer, thickness and composition of the pictorial layers, etc. On the other hand, the aging cracks start to form after the pictorial layers are dried. The cracks develop over the painting's lifetime, and as a result of the slow and gradual process their formation is affected by many environmental factors (Giorgiutti-Dauphiné and Pauchard 2016). Therefore, the delicate and intricate cracks, shaped by the painter's choice of materials, techniques, and the way the artwork was stored, may exhibit unique characteristics that are common to the artist's paintings which differ from those of other artists. As such, analyzing the painting cracks has become an important part of art examination, offering valuable information about the painting's authenticity (Barron and Sharma 2020; Pauchard and Giorgiutti-Dauphiné 2020); crack analysis is considered a technique to help determine the painting's origin and potentially establish a connection to a particular artist or period (Sidorov and Hardeberg 2019).

Some descriptive methods have been developed in the art conservation community as an effort to characterize the crack patterns and link those to the origins of paintings. Bucklow 1997 is widely regarded as the seminal work that pioneered a systematic approach for quantifying crack patterns and establishing their connection to the origin of paintings. Bucklow adopted a set of statistical and classification techniques to develop a formal description of painting cracks. As a result of the study, a collection of descriptive terms was developed to associate the crack patterns with the origins of paintings. The descriptions include the predominant direction, orientation, smoothness, straightness, thickness, and regularity of cracks, as well as the shape and size of islands enclosed by cracks. This approach was demonstrated, as shown in Table 1, to differentiate Italian, Flemish, Dutch, and French paintings created from different historical periods. Bucklow (1998) also utilized a repertory grid

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Table 1. Descriptive crack patterns associated with the origins of paintings (Bucklow 1997).

	Italian (fourteenth-fifteenth century)	Flemish (fifteenth-sixteenth century)	Dutch (seventeenth century)	French (eighteenth-nineteenth century)
Predominant direction	Often have	Nearly always have	Usually have	Usually do not have
Orientation	Usually perpendicular to grain	Usually parallel to grain	Usually perpendicular to longest side	N/A
Island size	Usually small to medium sizes	Usually very small sizes	Usually medium sizes	Usually large sizes
Island shape	N/A	Usually square	Often square	Usually not square
Smoothness	Usually jagged	Usually smooth	Usually jagged	Usually smooth
Straightness	N/A	Usually straight	N/A	Usually curved
Crack thickness	Sometimes distinct secondary cracks	Often uniform thickness of cracks	N/A	N/A
Regularity	N/A	Usually highly ordered cracks	N/A	N/A

approach to represent the structure of painting cracks in numerical ratings. This approach improved the quantitative aspect of the analysis and facilitated the comparison of crack patterns across different paintings and art-historical categories. Later, Bucklow (1999) introduced an image-based painting crack analysis whereby digitized crack images were segmented and converted into a set of Bezier curves for further analysis. The quantitative nature of this approach was recognized as a great advantage. However, a significant drawback was also highlighted: the prohibitive computational cost required for image processing, primarily due to the limited computing power available at the time of the research. Bucklow reported it took several months for the computer to represent 40 crack patterns, whereas it took 9 hours for the author to heuristically complete the representation of 528 crack patterns.

Since then, with significant advances in computing resources and algorithmic enhancements, image processing has become more feasible. In general, image processing involves the manipulation of digital images through mathematical algorithms with the goal of enhancing or extracting information from them. Image segmentation is an image processing technique that partitions an image into meaningful segments or regions based on color information, texture, or intensity gradients of the image. It is considered a critical step in many image processing applications, such as object recognition, classification, and tracking, as it enriches image data and enhances the accuracy of subsequent analysis. Image processing, including segmentation, has played a key role in the development of computer vision systems (Suri 2000). These advancements have transformed image-based crack analysis into a more systematic endeavor for 2D (Abas 2004; Spagnolo and Somma 2010) and 3D analyses (Kim et al. 2022). Recent studies in image-based crack analysis have focused on representing the painting crack network as a graph (Sidorov and Hardeberg 2019; Zabari 2021) and/or employing image-based deep learning techniques to learn and identify the crack patterns for further classification (Sindel, Maier, and Christlein 2021; Yuan et al. 2023).

Crack analysis is not exclusive to the field of paintings, but also an important research subject in geology and geological engineering. Existing cracks indicate broader geological processes at work, affecting the behavior of geo-materials such as rock and soil. Specifically, fractures refer to cracks resulting from geological and mechanical separations, such as those in rocks caused by internal or external stresses, including physical impacts and environmental conditions. Identification of fracture patterns in rock is important to better understand the geomechanical and hydrological behavior of the rock materials (Lei, Latham, and Tsang 2017). In addition to being indicative of past stresses and strains, physical crack properties such as crack shape, size, roughness, and connectivity can have significant implications for the stability and functionality of the materials. Recently, image-based analysis has become increasingly popular in the fields for crack identification in tandem with the advances in imaging techniques (Liu et al. 2013). Digital images have been heavily used to characterize soil desiccation cracks (Bordoloi, Ni, and Ng 2020; Liu et al. 2020, 2022; Zeng et al. 2022), and fractal analysis has been frequently conducted to assess cracking characteristics. For example, Hirata (1989) demonstrated the fractal structure of rock fracture geometry by using a box method to obtain the fractal dimension. This involved dividing the intricate crack web into a series of smaller square boxes, each with a side length of r.

$$N(r) \sim r^{-d} \tag{1}$$

$$f(cx) = \beta(cx)^{-d} = c^{-d}\beta x^{-d} = c^{-d}f(x) \propto f(x) \tag{2}$$

Hirata (1989) showed that r and the number of boxes $N(r)$ that crack enters follow a relationship as expressed in Equation (1), where d is the fractal dimension. When plotted on a log–log scale, a linear relation is realized with a slope of $-d$. More specifically, the presence of the linear graph in a log–log space signifies self-similarity across multiple scales. Mathematically, self-similarity manifests itself in a power-law as shown in Equation (2). A power function $f(x) = \beta x^{-d}$ that scales the argument x by a constant c results in a proportionate scaling of the function itself (Newman 2005), exhibiting a self-similar nature across different scales. This self-similarity has been observed in soil desiccation cracks (Baer, Kent, and Anderson 2009; Vallejo 2009; Goehring et al. 2015), which is discussed as an indication of distinctive characteristics associated with soil.

In view of this, two questions arise: would painting cracks display self-similarity as with soil desiccation cracks? And if so, could the characteristic self-similar trait of the cracks be linked to the provenances of paintings? These questions are currently difficult to answer due to the limited evidence available within the research community. Few studies have analyzed painting cracks to identify self-similarity. Eggert (2006) discussed the fractal geometries of cracks in artwork, which relate to glass rather than paintings. The objective of this study is to address the two questions above. The next section discusses the methodology, followed by a section examining the painting crack images presented in Bucklow (1997), focusing on the analysis of how the identified cracks from the methodology correlate with different paintings.

Methodology

Two approaches for crack analysis

When it comes to analyzing cracks in paintings, there are two possible approaches that can be employed. The first approach involves focusing directly on the crack network, while the second considers the characteristics of individual islands enclosed by the cracks. Figure 1 illustrates an example of an island. The first approach is more conventional, which has been adopted in most crack analyses, representing a crack network as a graph. On the other hand, the second approach is far less common. To our best knowledge, Bucklow (1997, 1998) and Freeman et al. (2013) are the only studies that attempted to analyze the island geometries in painting cracks. Our study will adopt the second approach, drawing an analogy between the discrete islands in painting cracks and the discrete soil clods (i.e. distinct clumps or aggregates of soil) in

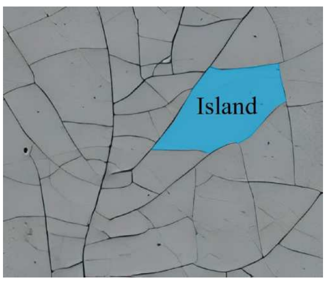


Figure 1. Example of an island enclosed by painting cracks (Image courtesy of Jeronimo Perez Roca – South Florida Art Conservation LLC (Roca 2013)).

desiccation cracks. To this end, we employ a methodology proposed by Lee et al. (2022), originally developed to analyze the geometries of soil particles. Specifically, it characterizes the *phenotypic trait* of the particles, showing that the trait exhibits a pattern in log–log space, which can be formulated as a power function, as in Equation (2). In light of the findings, our study aims to characterize the phenotypic trait of the islands by adapting the methodology in Lee et al. (2022) to answer the afore-stated two questions. It is worth noting that the phenotypic trait is a geometry concept that goes beyond shape and size; it extends to the underlying properties associated with those. As an analogy, people of an ethnic origin may have some variations in their appearances but share a phenotypic trait due to a common genetic origin and biological history. For example, while each Korean woman possesses a distinct facial appearance, they also share a common phenotypic trait that stems from their shared genetic origin. This phenotypic trait sets them apart from women of other origins, who have different genetic backgrounds and exhibit their own unique set of characteristics. Likewise, mineral particles that originate from the same geologic origin and experienced the same history possess a shared phenotypic trait, despite exhibiting variations in their shapes and sizes. Similarly, the painting cracks and the islands share a common origin attributed to the use of specific materials and painting techniques, as well as the history of drying and aging. Given the similarities, we may hypothesize the existence of a common phenotypic trait behind the formation of crack islands in paintings created by the same artist.

Phenotypic trait of 3D geometries

Lee et al. (2022) reported that a power-law relationship exists between the surface area-to-volume ratio ($\underline{A}/\underline{V}$)[1] and the volume ($\underline{V}$) for a family of particles having a common geologic origin and history. Graphically, the data points realize a linear relationship between $\underline{A}/\underline{V}$ and $\underline{V}$ in a log–log space, which indicates the presence of a phenotypic trait of the 3D particle geometries. A demonstration is shown in Figure 2. The set for analysis contains 100 Florida limestone particles from Tripathi et al. (2023). The particles were individually scanned using a Polyga C504 structured light 3D scanner, providing a high resolution and accuracy down to 6 microns (Polyga 2021). The scanner, positioned directly above a particle, captured its 3D geometry by taking images from multiple angles as the particle was rotated and flipped, ensuring thorough scanning of all surfaces. Typically, 15–20 scans were conducted per particle to ensure comprehensive coverage. The individual scan images were then merged to construct a 3D digital representation of the particle. Finally, Blender (2022), a 3D graphics software, was utilized

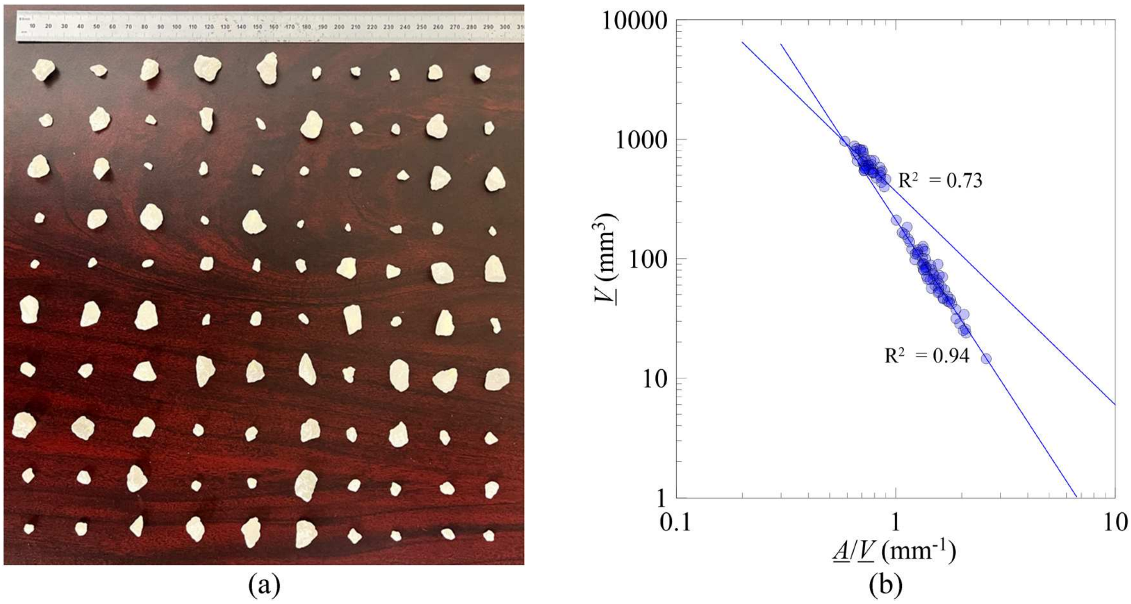


Figure 2. A demonstration to uncover phenotypic traits: (a) 100 Florida limestone particles; and (b) Two phenotypic traits of particle geometries uncovered in terms of $\underline{A}/\underline{V}$ and $\underline{V}$.

to measure the 3D geometrical attributes of the digitally represented particle including surface area ($\underline{A}$) and volume ($\underline{V}$). Further details on the scanning and digitization processes can be found in Tripathi et al. (2023).

The 100 Florida limestone particles consisted of two different groups of particles, each originating from distinct sources (Figure 2(a)), yet their distinct identities elude the naked eye. However, a power regression analysis on the $\underline{A}/\underline{V}$ and $\underline{V}$ geometry data brings to light the presence of two coherent data clusters. These data clusters exhibit two distinct linear relationships in the log–log space (Figure 2(b)). They are positioned at dissimilar locations with different variations. The coefficient of determination (R^2) for each group is calculated as 0.73 and 0.94, respectively. The dataset located in the upper region of the plot, characterized by larger values of $\underline{V}$, corresponds to the larger particles, while the data in the lower region represent smaller particles. The data orientations, as represented by the power regression slopes, depend on the relationship between particle shape and size of each group. These serve as identifiers that unveil two distinct phenotypic traits exhibited by the particles, much like genetic footprints. This suggests that this group comprises a mixture of two different kinds of particles.

Phenotypic trait of 2D geometries

The methodology by Lee et al. (2022), introduced above, was originally developed to analyze 3D geometry. This study adapts and develops a 2D equivalent concept to reveal the phenotypic trait of the island geometries, whereby the 2D island area (A) is used in the place of 3D particle volume ($\underline{V}$), and the 2D island perimeter (P) substitutes 3D particle surface area ($\underline{A}$). This study therefore examines whether a phenotypic trait presented by the perimeter-to-area (P/A) and area (A) data can be correlated with the provenances of paintings. Another modification in this study is the utilization of bivariate ellipses to comprehensively represent the location and variation of the data. For consistency in utilizing the bivariate ellipse, the eigenvector of the ellipse is also employed to indicate the orientation of the data, thus eliminating the need for a separate adoption of a power regression line as employed by Lee et al. (2022) and illustrated in the example above (Figure 2(b)). Although the slope of the eigenvector may exhibit a slight difference compared to that of the power regression, both remain proportionate. Therefore, it is deemed suitable for the purpose of this study.

$$C_P = P_C/P \tag{3}$$

$$C_P^2 = C_{Cox} = 4\pi A/P^2 = 4\pi \times (P/A)^{-2} \times A^{-1} \tag{4}$$

The P/A and A data are also useful for characterizing the 2D shape, particularly in terms of *perimeter circularity* (C_P) (Tripathi et al. 2024). Circularity measures how closely a 2D shape resembles a perfect circle, with values ranging from 0 to 1, where 1 represents a perfectly circular shape. As shown in Equation (3), C_P quantifies a 2D shape by comparing the 2D object's perimeter (P) to that of a circle with the same area (P_C). The square of C_P is formulated as shown in Equation (4), which corresponds to C_{Cox} as defined by Cox (1927). Using the relationship $P_C{}^2 = 4\pi A$, C_P and C_{Cox} can be obtained with P/A and A. Therefore, the

P/A and *A* data of 2D objects can be directly utilized to measure circularity.

Analysis

Images of painting cracks

This study analyzes the crack images of Italian, Flemish, Dutch, and French paintings from the fourteenth to the nineteenth centuries collected by and presented in Bucklow (1997). Table 2 presents a summary of the origins and descriptions of all seventeen images in Bucklow (1997). Please note that the figures in Bucklow (1997) are referred to as 'Image,' while the figures in this paper are labeled as 'Figure' to avoid confusion. The specified horizontal dimension in the table indicates the length scale of each Image. The qualitative description by Bucklow is also presented in the table.

Analysis procedure

The workflow adopted for this study is shown in Figure 3. Various image-based methods for crack detection have been developed, and the workflow presented in Figure 3 may be seen as a variation of those image-based crack detection methods. The major adaptation is the detection and characterization of the individual islands enclosed by painting cracks, shifting the focus from the cracks themselves, which has been the common emphasis in the existing methods. Recent comprehensive reviews, including the one by Munawar et al. (2021), have reported generally excellent performance in crack detection using currently available algorithms. These findings suggest that inaccuracies likely stem from camera resolution rather than the detection algorithms. Consequently, if cracks are adequately presented in an image, modern algorithms are generally capable of detecting them effectively. Since the images in Bucklow (1997), taken more than two decades ago, may not clearly present the hairline cracks, Step 1 involves enhancing the quality of these images using an artificial intelligence (AI)-powered image processing tool (Pickwish 2023). The purpose of this enhancement is to clearly depict the boundaries of the islands, facilitating an improved image segmentation process.

The image segmentation process (Step 2) involves converting the original crack images into binary images. The converted black and white binary images are shown in Figure 4, where the islands are represented as white pixels and the cracks are represented as black pixels. Image Segmenter app (MathWorks 2021a), a MATLAB image processing toolkit, is then utilized for segmenting the crack images, thereby identifying the individual islands within each image. The effectiveness of this segmentation procedure using the Image Segmenter app has been demonstrated in the authors' previous study (Abu-Haifa and Lee 2022, 2023).

The boundary of each segmented island is then captured using the MATLAB boundary tracing function, *bwboundaries* (MathWorks 2021b), and represented as a polygon (Step 3). The vertices of the polygon, representing the boundaries of the polygonal islands, are given in pixels. On average, each island is represented by more than 100 vertices, ensuring a sufficient level of detail for accurately depicting the geometries. In Step 4, the islands are scaled to their actual sizes (i.e. pixels are converted to *cm*) based on the horizontal dimension provided in Table 2.

Table 2. Descriptions of all seventeen images presented in Bucklow (1997).

Image #	Origin	Painter	Painting	Horizontal dimension, d_h (cm)	Description of crack pattern
1	French	Nicolas de Largillière	*Study of Hands*	7	No direction
2	Flemish	Hieronymus Bosch	*Christ Mocked*	4.5	Parallel to the wood grain
3	Italian	Paolo Uccello	*The Battle of San Romano*	4.5	Perpendicular to the wood grain
4	Dutch	Frans Hals	*Portrait of Woman with a Fan*	7	Jagged and straight cracks with square islands
5	French	Alexandre Gabriel Decamps	*The Caravan*	7	Smooth and curved cracks, and not square islands
6	Italian	Sandro Botticelli	*Four Scenes from the Life of Saint Zenobius*	4.5	Small islands
7	Italian	Master of the Fogg Pieta	*Saint Lawrence*	4.5	Large islands
8	French	Francois Boucher	*Venus Asks Vulcan for Arms for Aeneas*	7	Cracks of uniform thickness
9	Italian	Paolo Uccello	*The Battle of San Romano*	4.5	Secondary network
10	Dutch	Johannes Lingelbach	*The Army of Charles II*	7	Connected network
11	Italian	Duccio	*Annunciation*	7	Broken network
12	Flemish	Master of St Giles	*Saint Giles*	4.5	Ordered network
13	French	Francois Boucher	*Diana Bathing*	7	Random network
14	Italian	Lorenzo Monaco	*The Coronation of the Virgin*	4.5	Typical pattern for an Italian fourteenth/fifteenth-century painting on panel
15	Flemish	Robert Campin	*Virgin and Child before a Firescreen*	4.5	Typical pattern for a Flemish fifteenth/sixteenth-century painting on panel
16	Dutch	Jan van de Cappelle	*River Scene with a Large Ferry*	7	Typical pattern for a Dutch seventeenth-century painting on canvas
17	French	Jean Simeon Chardin	*The House of Cards*	7	Typical French eighteenth-century painting on canvas

Figure 3. Workflow to analyze the phenotypic trait of painting cracks.

In Step 5, the geometrical information (i.e. area A and perimeter P) for each island is determined from the polygons using the built-in MATLAB functions, *polyarea* and *perimeter* (MathWorks 2023a, 2023b). In case a partial crack is present within an island, as illustrated in Figure 5(a), a threshold crack width of 2 pixels is utilized to determine whether the partial crack should be included as part of the boundary. If the width of the partial crack is at least 2 pixels, it is considered part of the boundary and included (Figure 5(b)), otherwise it is excluded (Figure 5(c)). Lastly, the phenotypic trait is analyzed in terms of the P/A and A data (Step 6).

Results and discussion

The phenotypic traits of painting cracks in all 17 images are presented in Figure 6, shown on log–log

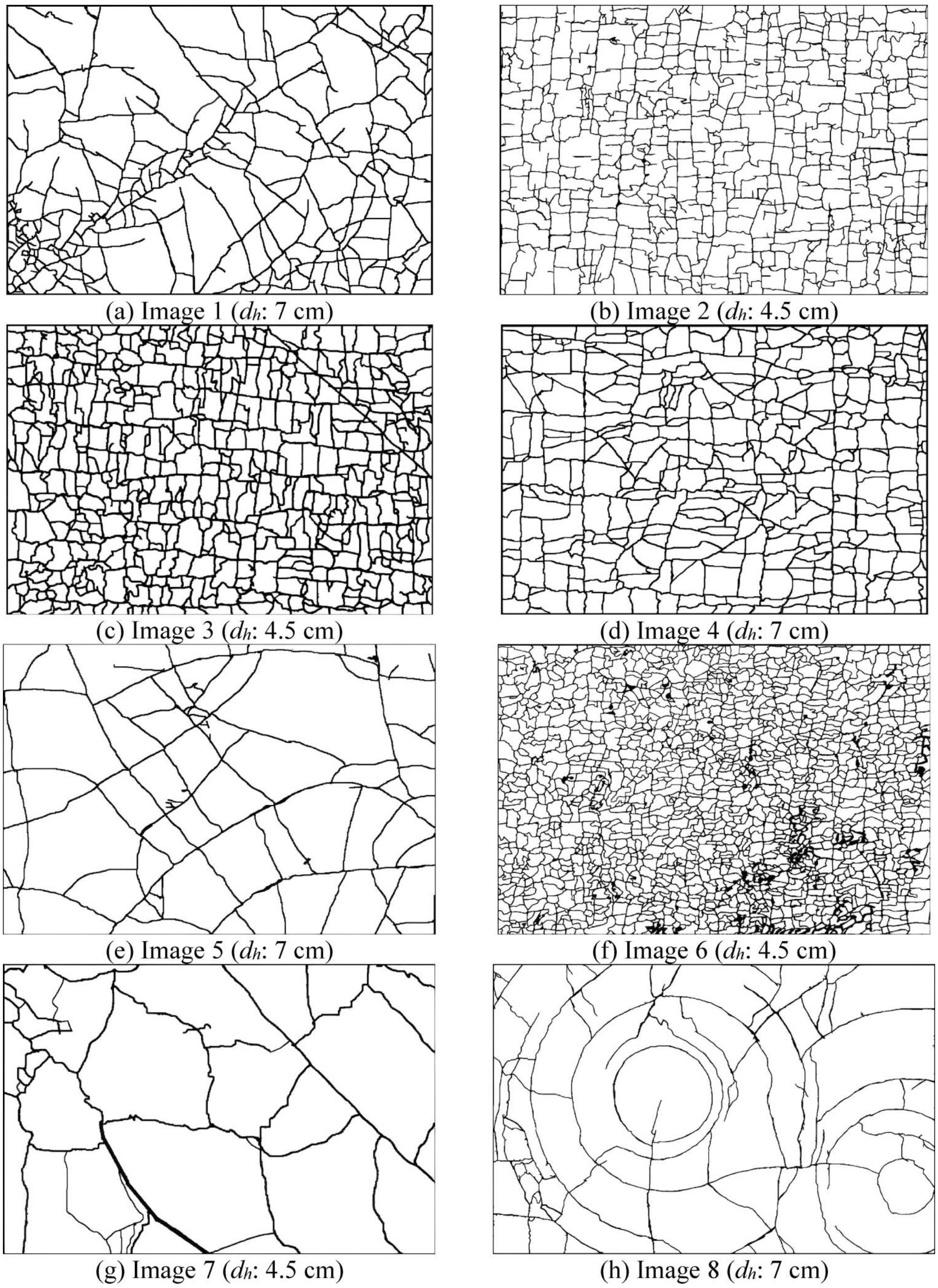


Figure 4. Binary crack images, where d_h indicates the horizontal dimension of image.

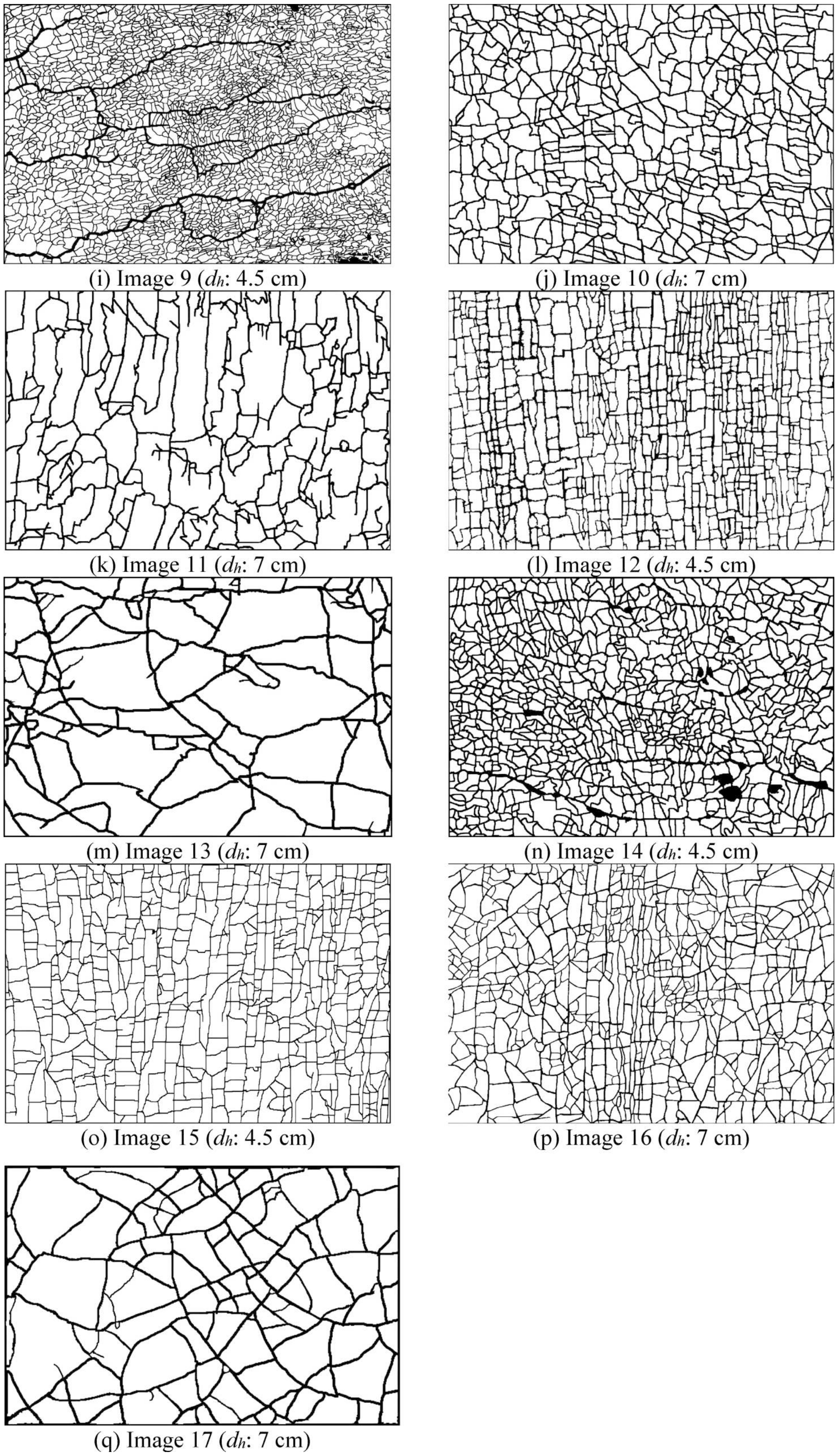


Figure 4 *Continued*

scales, using the *P/A* and *A* data of the islands within each image. The values along each axis are presented on a logarithmic scale with a base of 10. For example, 0 in the axes indicates the numerical value 1 ($= 10^0$). The scale range is set to be sufficiently large, ensuring consistency across all images. The length units are *cm*, so the unit of *P/A* is cm^{-1}. A bivariate ellipse is plotted to provide a comprehensive representation of the data's location, orientation, and variance determined by the statistical properties of the data and the chosen confidence level (Van Houwelingen, Zwinderman, and Stijnen 1993). To construct probability

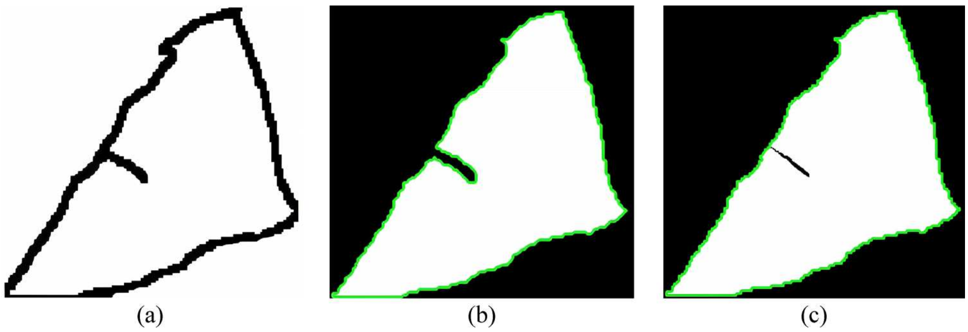


Figure 5. Determination of island boundary: (a) Presence of a partial crack; (b) A partial crack is considered part of the boundary (in green) if the width is at least 2 pixels; and (c) A small crack is not considered as part of the boundary.

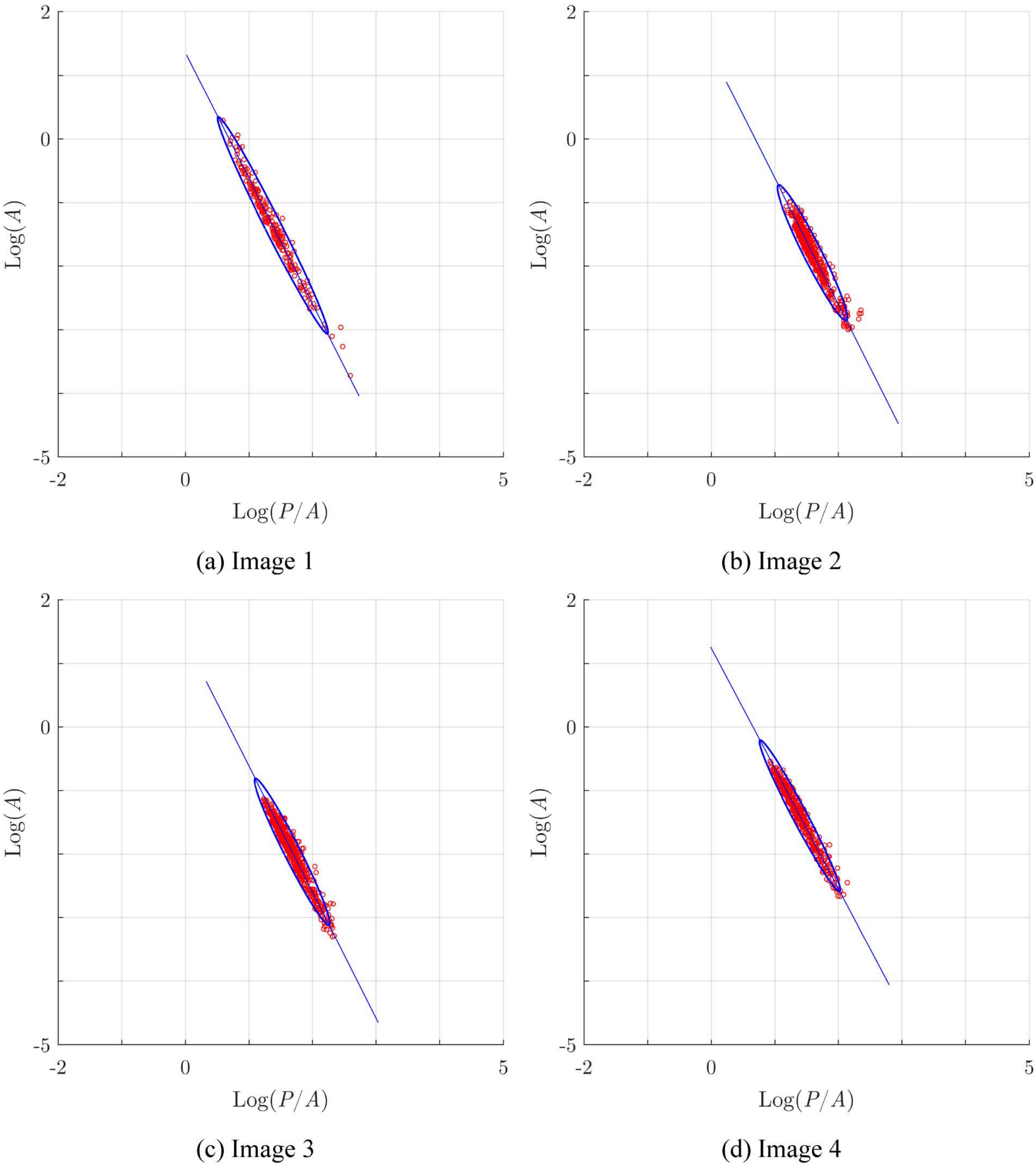
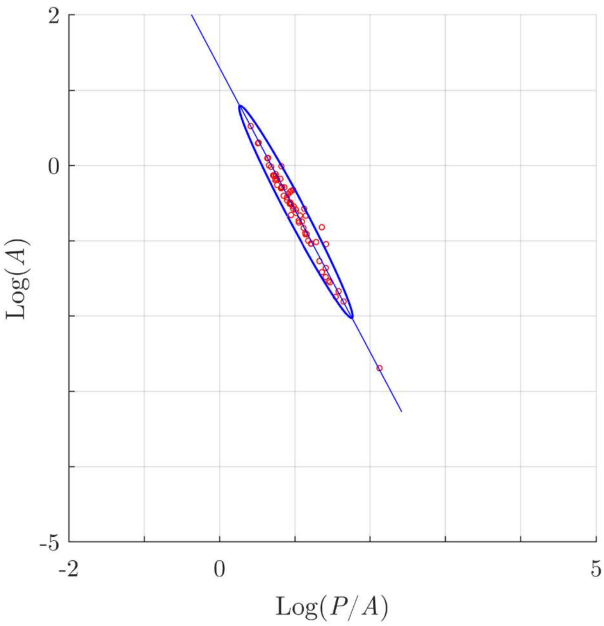
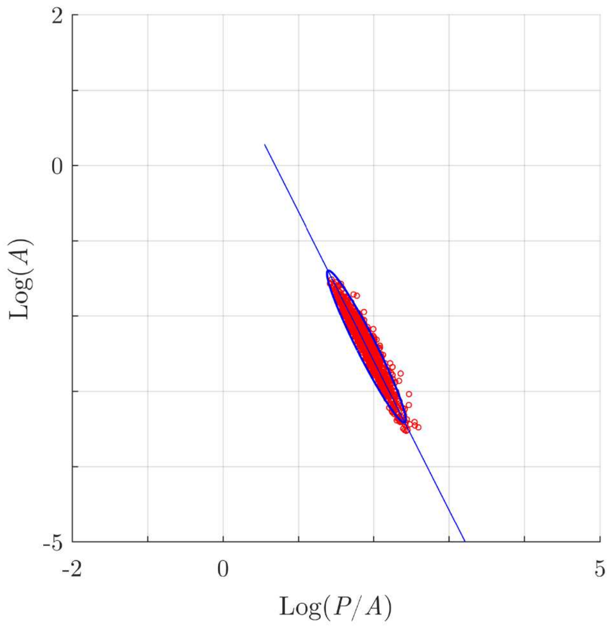


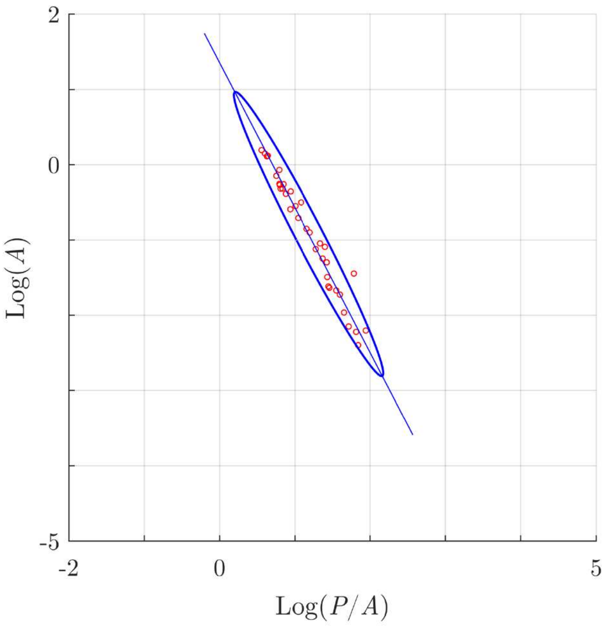
Figure 6. Phenotypic traits of painting cracks, presented by the *P/A* and *A* data.



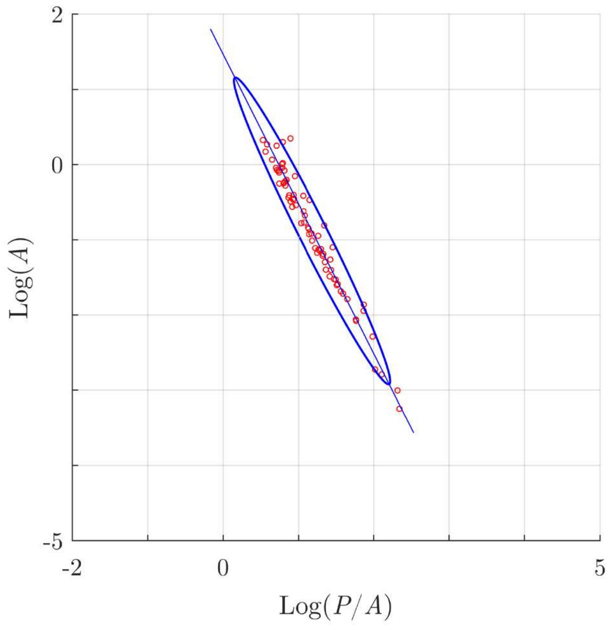
(e) Image 5



(f) Image 6



(g) Image 7



(h) Image 8

Figure 6 *Continued*

ellipses for a bivariate distribution at a given confidence level, the process begins by calculating the means of both data sets and their covariance matrix. Each ellipse is then centered around the means and aligned according to the direction of the first eigenvector of the covariance matrix, which represents the direction of maximum variance. The length of the primary axis of each ellipse is determined by the square root of the percentile of the chi-squared distribution corresponding to the desired confidence level. All bivariate ellipses in this paper are constructed with the estimates performed at a 99% confidence level. While the ellipse represents the overall trend, variance, and uncertainty of the data, the distribution within the ellipse might appear asymmetrical. This asymmetry occurs because the ellipse is shaped based on the covariance matrix and the chi-squared value, which primarily capture the global properties of the dataset rather than localized variations or distinct clusters.

As demonstrated in Figure 6, each data point, representing the geometry of a crack island, aligns in a coherent linear relationship within the log–log space. The eigenvector of the ellipse is plotted to enhance the visualization of the orientation. This linear alignment, indicative of a power-law relationship between these quantities, suggests that the system exhibits scale invariance, a hallmark of self-similar structures. This implies that painting cracks, like other natural

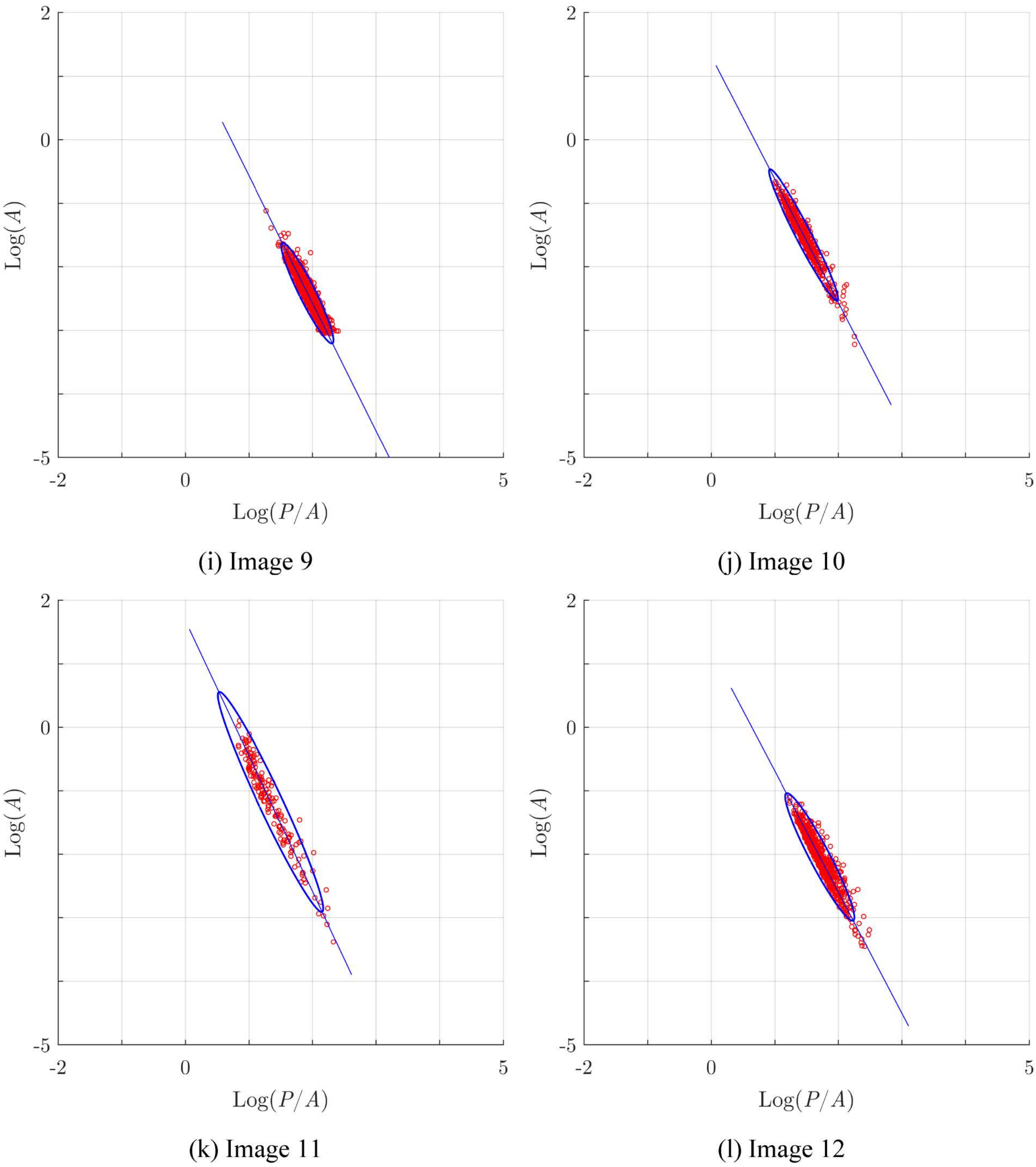
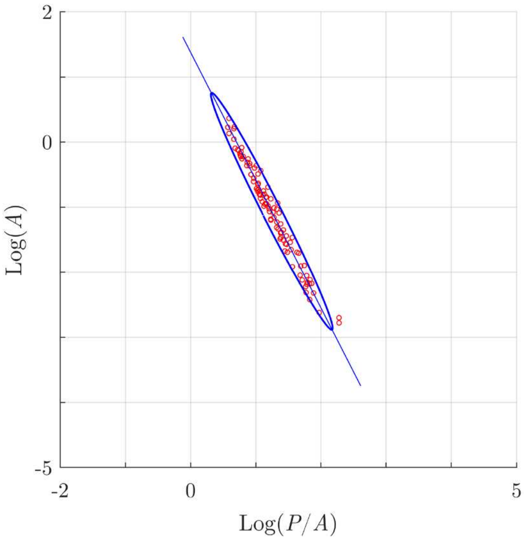


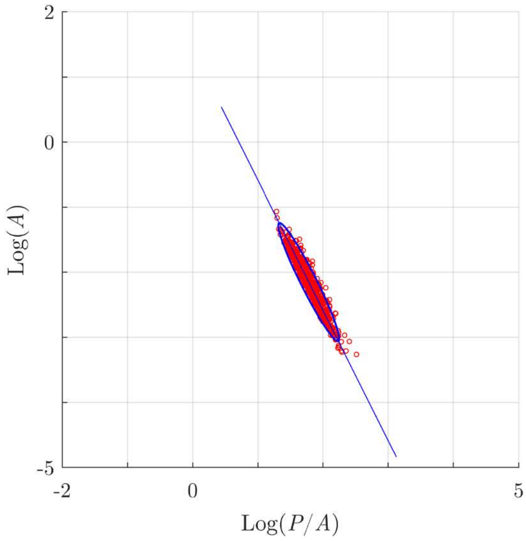
Figure 6 *Continued*

formations such as soil desiccation cracks, also exhibit the characteristic feature of self-similarity. The slope of the power-law in a log–log plot, hovering around −1.9, suggests a specific scaling behavior consistent across different scales. These observations thus address the first research question posed in this paper.

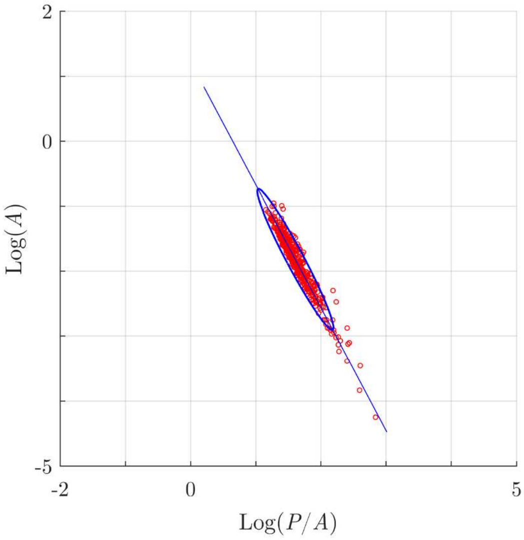
The MATLAB functions, *polyarea* and *perimeter*, used to measure *A* and *P* data of the islands, essentially rely on pixel counting and distance summation of boundary pixels, respectively. Given that the island sizes in the images are typically much larger than the crack width, the pixel counting method to estimate the island area is deemed sufficiently accurate (Liu et al. 2011). However, estimating the perimeter of islands is complex due to the fractal nature. This complexity mirrors the coastline paradox, famously explored by Lewis Fry Richardson (1961) and further articulated by Benoit Mandelbrot (1967). The paradox demonstrates that the measured length of a coastline, or similar fractal geometries such as cracks, increases as the size of the measuring unit decreases. Mandelbrot noted that the fractal dimensions of coastlines usually range between 1 and 2, which reflects the increase rate in measured length with finer measurements. Liu et al. (2011, 2013) proposed a method using line segments to measure the perimeter by connecting 'key' pixels in a crack image. They reported that this line segment method provided a more



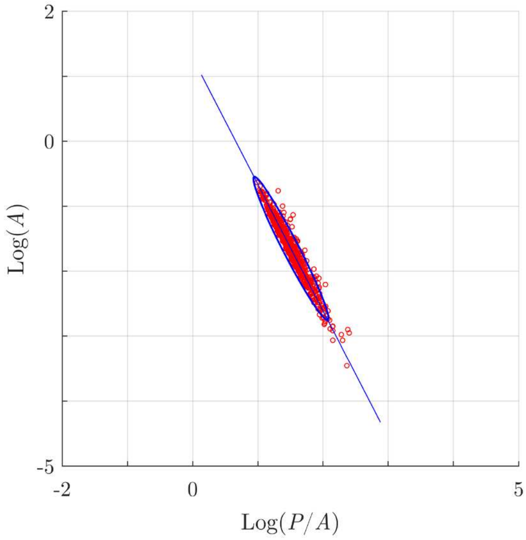
(m) Image 13



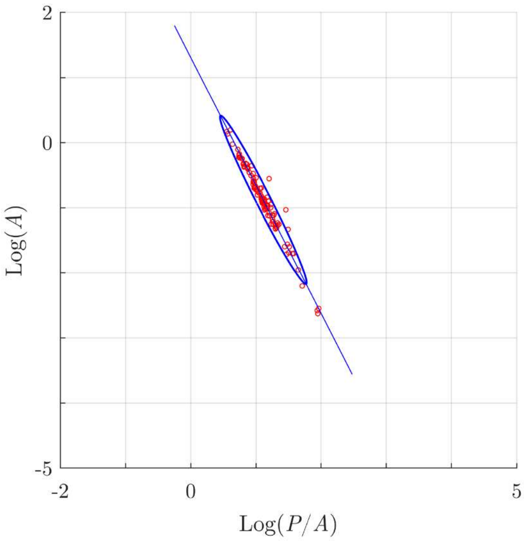
(n) Image 14



(o) Image 15



(p) Image 16



(q) Image 17

Figure 6 *Continued*

accurate perimeter measurement, as the conventional method of summing distances of 'all' boundary pixels could overestimate the perimeter by 5% or more. However, the line segment method does not account for the fractal nature of cracks; from the perspective of fractal analysis, employing such longer line segments that connect 'key' pixels (i.e. coarser measuring units) could lead to an underestimation of the perimeter. While further research is needed to address the error estimation in perimeter measurements, the geometric data presented in Figure 6 effectively capture self-similar fractal characteristics, akin to those observed in other natural formations. This therefore supports the validity of the measurements used in this study.

The bivariate ellipses are used to address the second research question posed in this paper. Specifically, this investigation explores whether the phenotypic trait exhibited by the *P/A* and *A* data can exhibit characteristics associated with the provenances of the paintings. Figure 7 illustrates the ellipses estimated for the crack images from Flemish paintings (Images 2, 12, and 15). Figure 8 presents those for Dutch paintings (Images 4, 10, and 16), and Figure 9 shows the ellipses estimated for the crack images from Italian paintings (Images 3, 6, 7, 9, 11, and 14). Those for French paintings (Images 1, 5, 8, 13, and 17) are presented in Figure 10. Figure 7 shows evidence of comparable ellipses for the Flemish paintings. Figure 8 also supports this finding by demonstrating that paintings originating from the same source exhibit similar ellipses, suggesting the presence of shared phenotypic traits influenced by the provenance of the paintings.

On the other hand, Figure 9 reveals the presence of two distinct sub-groups, A and B, within the Italian paintings, with the ellipses indicating that the physical characteristics of the painting cracks exhibiting clear differences between them. As shown in Figure 4, Images 3, 6, 9 and 14 (sub-group A) commonly feature small to medium-sized islands. In contrast, Images 7 and 11 (sub-group B) display much larger islands, with some instances of a broken crack network. Please note the horizontal dimension d_h of Image 11 is 7 cm, which is larger than the others. The variations in cracks can be attributed to many factors, including the age of paintings, the specific materials used, the painting techniques employed by the artists, and the environmental conditions present during the creation and preservation stages (Flores 2018; Elkhuizen et al. 2019; Maev, Baradarani and Taylor 2020). All paintings in the sub-group A are by painters who were born, trained, and worked in Florence (Berti 1964; Roy and Gordon 2001; Gloria 2004; Higgitt and White 2005). On the other hand, little is known about the Master of the Fogg Pieta, who painted *Saint Lawrence* (Image 7), and Duccio, who painted *Annunciation* (Image 11), worked in Siena (Harvard Art Museums 2014; Carli 2024). Another key differentiator between the Italian sub-groups A and B is clearly the age of the paintings; sub-group A corresponds to paintings created in the fifteenth century, while sub-group B represents paintings from the early fourteenth century (Robb 1936; Fehm 1976; Griffiths 1978; Dunkerton and Roy 1996; Bucklow 1997).

While the bivariate ellipse effectively aids in quantifying traits to interpret crack patterns in paintings – such as those found in the sub-groups of Italian paintings – it may not conclusively pinpoint provenances. For instance, ellipses from Images in Italian sub-group A show some similarities to those in Flemish paintings (Figure 7), while ellipses from images in

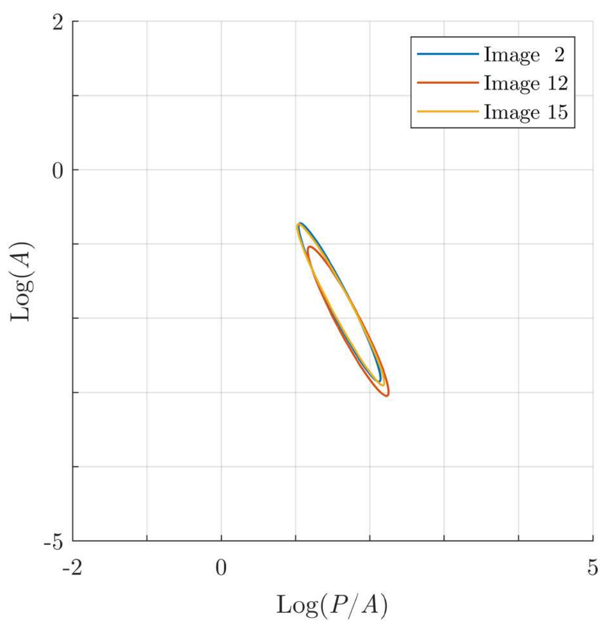


Figure 7. Bivariate ellipses estimated for the crack images from the Flemish paintings.

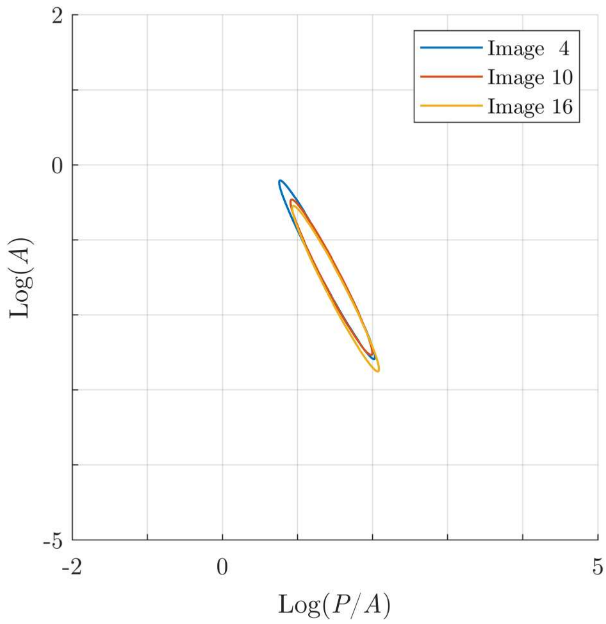


Figure 8. Bivariate ellipses estimated for the crack images from the Dutch paintings.

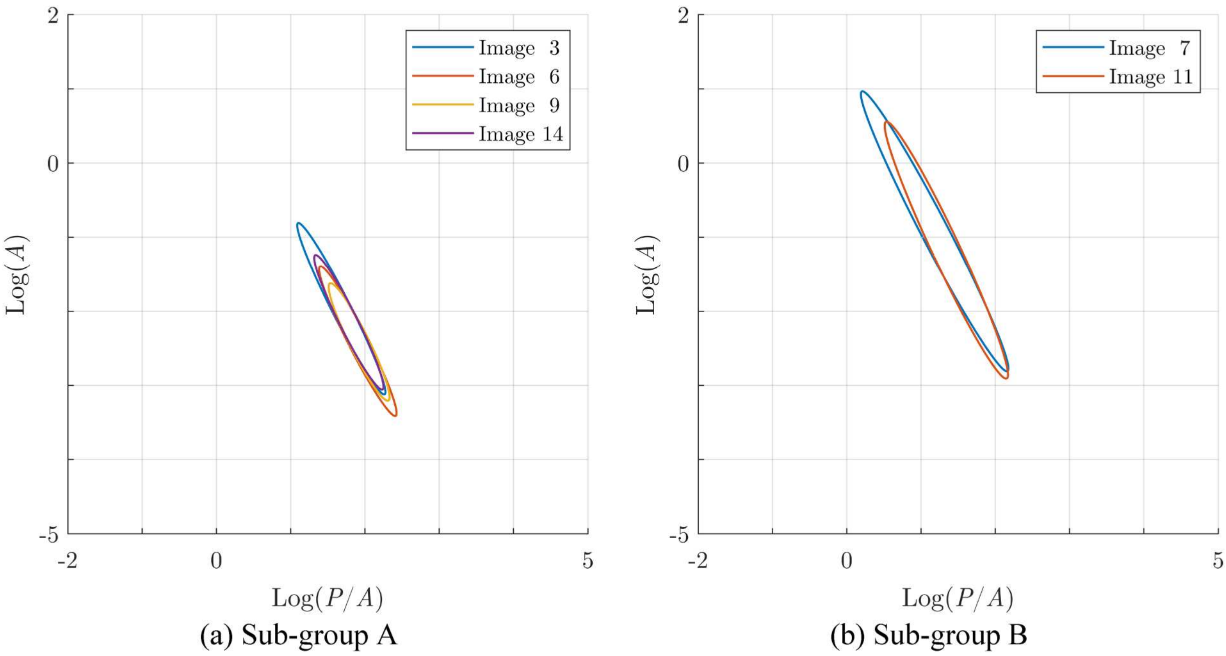


Figure 9. Comparable bivariate ellipses within each sub-group of the Italian paintings.

Italian sub-group B resemble one of the sub-groups in French paintings (Figure 10(a)).

In French paintings, it is observed that the cracks form larger islands compared to paintings of different origins, as shown in Figure 4, resulting in data with correspondingly large area *A*. Consequently, the ellipses representing these islands occupy the plot space associated with high *A* values (Figure 10). The French paintings also have sub-groups. The cracks in Images 1, 8, and 13 (Figure 10(a)) show similar phenotypic traits, leading to comparable ellipses. Likewise, Images 5 and 17 (Figure 10(b)) exhibit comparable traits and ellipses. As with the Italian paintings, the trend suggests that paintings created within the same century tend to exhibit similar traits in cracks. Images 1, 8, and 13 correspond to paintings created in the eighteenth century (Meyer 1995; Ledbury and Hyde 2006; Louvre Museum 2014), while Image 5 is from the nineteenth century. Image 17 is from the eighteenth century but has a different provenance from the other French paintings, which may have influenced the aging crack formation and, consequently, the attributes of the bivariate ellipses, placing it in sub-group B. While the other French

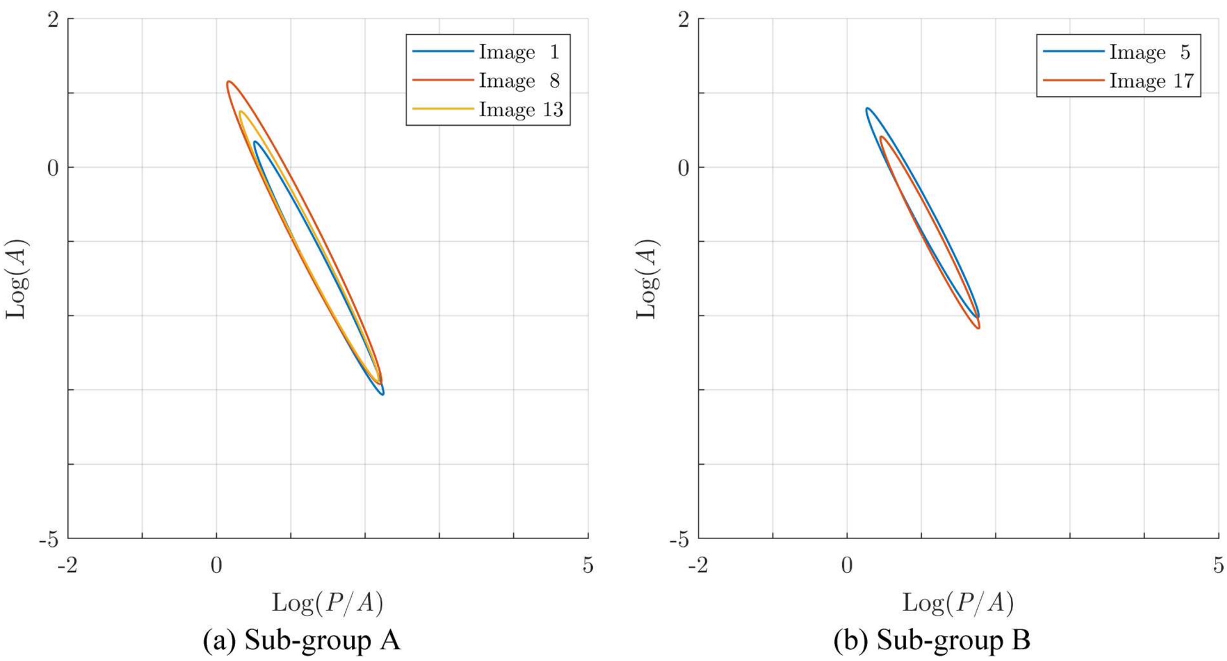


Figure 10. Comparable bivariate ellipses within each sub-group of the French paintings.

paintings have been collected and stored in the Louvre, *The House of Cards* (Image 17) became part of the collection of Catherine II, Empress of Russia, after it was painted in 1737 and was housed at the Imperial Hermitage Gallery in Saint Petersburg, Russia. It remained in the Hermitage until Andrew W. Mellon purchased it in 1931 and later gifted it to the National Gallery of Art in Washington, DC, in 1937 (The National Gallery of Art 2016). As a result, the painting underwent preservation practices distinct from those of the other French paintings.

Concluding remarks

This paper introduces a new perspective on painting cracks, also known as craquelure, investigating two questions: Do painting cracks exhibit self-similarity? And if so, can the characteristic self-similarity of these cracks be correlated with the provenances of paintings? To this end, we employ the concept of the phenotypic trait of painting cracks, with a specific focus on the 2D geometries of islands enclosed by cracks. A set of 17 crack images from French, Italian, Flemish, and Dutch paintings, available in Bucklow (1997), which span the fourteenth to nineteenth centuries is analyzed. Digital image analysis techniques, including image segmentation and boundary detection, are utilized to extract the 2D geometrical features from the images.

This study evidences a power-law relationship between perimeter-to-area (*P/A*) and area (*A*) data of the islands in a log–log space. This power-law relationship highlights the inherent self-similar nature present behind the various painting crack patterns. Bivariate ellipses and their eigenvectors are employed to provide a comprehensive representation of the location, variance, and orientation of the island geometry data. The study finds that comparable ellipses tend to emerge when cracks exhibit similar phenotypic traits, particularly in cases where paintings share an origin and similar painting techniques, and undergo common preservation practices. Therefore, these phenotypic traits appear to reveal characteristics that can be associated with the provenances of the paintings. It is important to note that establishing a universal measure to pinpoint the origin of a painting solely based on its cracks remains a challenge. This difficulty arises due to variations in preservation practices, including storing and handling, which can influence the development of aging cracks over time. Nevertheless, the comparative study presented in this paper provides compelling evidence supporting the validity of the proposed approach that utilizes the *P/A* and *A* data of islands.

This study analyzes the images from Bucklow (1997), thus limiting its scope to the samples documented therein. Bucklow's investigation focused on small segments of entire paintings, and our study similarly concentrates on these segments. A question, then, is the reliability of analyzing such small segments, as they may not represent the characteristics of the entire painting. This was not fully addressed in our study, yet the promising results encourage further exploration. For example, both Images 3 and 9 are from *The Battle of San Romano*, and they are successfully categorized within the same sub-group using the proposed analysis method. A limitation of this study is that the craquelure analysis applies only to paintings with discernible cracks that can be segmented into distinct islands. We avocate for further research with expanded image sets and a more comprehensive examination of multiple crack patterns that may be present within the same paintings to assess the broader applicability of the proposed approach. Therefore, we invite the research community to further explore the approach to unlock the potential for elucidating the phenotypic traits of painting cracks.

In addition to the field of scientific examination of artworks, the findings in this paper have far-reaching significance. The approach employed in this study introduces a new paradigm for crack analysis, emphasizing the examination of islands formed within cracks. By shifting the focus from the crack network itself, this approach offers a departure from conventional crack analyses and will open up new avenues for understanding the physical characteristics and underlying mechanisms of cracks.

Note

1. For clarity, hereafter, symbols with an underscore are used to denote 3D geometric properties, while symbols without an underscore indicate 2D properties. For example, $\underline{A}$ represents a 3D object's surface area, while *A* represents a 2D object's area.

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Data availability

Data is available from the authors upon request.

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